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Paper

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Working Paper Series

#5

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Can't Keep Up with the Joneses

How Relative Deprivation Pushes Internal Migration in Austria

Can't Keep Up with the Joneses: How Relative Deprivation Pushes Internal Migration in Austria^{*}

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Working Paper

Abstract

We estimate the effect of regional income inequality on emigration rates of Austrian municipalities using a unique data set that is constructed based on individual level data from Austrian administrative registers. The register-based data contains information on the municipality of residence of all individuals aged 16 and over that have their main residency in Austria, as well as their income and socio-demographic characteristics. Aggregating this information to the municipality level allows us to assess the role of relative deprivation—a measure of relative income—on top of absolute income in shaping internal migration in Austria. We find that increases in relative deprivation in a municipality lead to higher emigration from the municipality. Allowing for heterogeneous effects across income, education, and age groups reveals that the effect is stronger among those with comparably low levels of income, and among low skilled and young individuals.

Keywords: Relative Deprivation, Inequality, Internal Migration

JEL Classification Codes: D31, R23

1 Introduction

Why do persons migrate? The decision to migrate has most commonly been modeled as a cost-benefit conundrum, where the costs of migration (e.g. geographic distance) and the associated benefits (differential income, remittances, consumption possibilities) are weighted against each other and, given a positive financial balance, induce migration. More recently the *New Economics of Labour Migration* has extended this narrow perspective, and improved upon classical approaches. It does so by extending the set of possible drivers of migration to social, behavioral and other non-labor market factors, which may be relevant for individuals' utility functions (Stark and Bloom, 1985).

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For example Stark (1984) and Stark and Taylor (1989) argue, that the self-perceived position of a person/household within a society may influence migration propensities. This implies that individuals do not necessarily migrate to achieve absolute income gains alone, but also to improve their position with respect to a particular reference group in a society. This argument is based on the concept of *relative deprivation* (RD), which represents a discontent that results from having an income lower than that of a certain comparison group (Runciman, 1966). This idea of RD is closely related to the concept of the *relative income hypothesis* proposed by Veblen (1899) and Duesenberry (1949). Despite the fact that both theories focus on a similar aspect—the comparison of individuals with those higher up the social ladder—they constitute two separate strands in the literature. Some authors note that relative deprivation is just an operationalisation to test the relative income hypothesis (Stark and Taylor, 1991). Others argue that the concept of relative deprivation takes a more general approach, insofar as it provides an overall theory of social status, while the relative income hypothesis was mainly phrased in terms of individual savings (Verme, 2013).

The measurement of RD could be based on a cardinal as well as an ordinal scale, the latter being used, e.g., in the influential work on poverty by Sen (1976) or as has been argued most recently by Stark (2017). Although ordinal measures of RD seem to be an appealing approach, they do however require individual level data for an appropriate implementation. Thus, this concept has been rarely addressed in migration contexts. In contrast, Yitzhaki (1979) suggests a cardinal measure for individuals by calculating the mean excess income times the share of individuals in the reference group that have higher incomes. Based on this definition, individuals can lower their RD by either changing their income level or their reference group. Through these two channels high RD can *inter alia* induce harder work or it can increase the propensity to migrate, respectively (Stark, 2006).

In the latter case, migration can be regarded as an attempt of improving one’s relative position across the income distribution with respect to a certain reference group. Given that absolute income remains unchanged, this can be achieved by moving to a region where the individual ranks higher in the income distribution. In doing so, households can substitute their original reference group for a new reference group at the migration destination. However, such a substitution process requires a certain degree of social and cultural homogeneity and is in general assumed to be time consuming (Stark and Taylor, 1991). Contrary to that, highly skilled migrants are more likely to substitute their reference group in shorter periods of time, based on the argument that they integrate more easily and are better informed about their new residence (Czaika and de Haas, 2012).

Since their introduction, both arguments, relative deprivation and the relative income hypothesis, have triggered a large number of empirical studies, that shed light on the perceived inequality of individuals. Although both approaches present very similar ideas, effects on migration have largely been studied for the concept of RD. A central feature of RD concerns the definition of a reference group, which individuals compare themselves to. Besides quantifying the effect of this kind of inequality on emigration propensities, a major focus is thus the identification of reference groups for different subsets of migrants. Furthermore, the concept of RD implies some definition of “neighbourhood”, be it socially (beliefs), economically (education) or geographically (space).

Covering all these aspects is in general a complex task, since the data requirements in terms of population coverage, available variables and spatial aggregation levels are typically beyond the information levels surveys and similar data sets can provide. A methodology to overcome the shortage of internal migration data availability is presented by Smith, Raymer, and Giuli-etti (2010) and Raymer, Abel, and Smith (2007) in combining data from different sources. However, due to the data limitations, many studies resort to analysing special topics, such as

cross-country/-border migration or population subsets, often using aggregated data to calculate RD.

In this paper we examine the impact of inequality and households' relative income position within local communities on emigration flows across these municipalities for Austria. This unique spatially disaggregated perspective is based on novel individual level panel data from Austrian administrative registers, which comprehensively capture the economic situation and geographic movements of the whole Austrian population. Besides the overall effect of inequality on emigration rates, these data further allow us to examine which social groups are especially sensitive to inequality and what their reference groups are.

Stark (2006) provides an analytical explanation for the positive relationship between income inequality (measured by the Gini coefficient) and the incentive for migration by focusing only on income inequality at the origin, irrespective of income inequality at the destination. In this way households or individuals who feel more relatively deprived exhibit a higher propensity to migrate, if the income distribution at the origin becomes more unequal, given some fixed income distribution at the destination. This further results in adverse selection of migrants, since individuals who feel more relatively deprived tend to be less educated and exhibit a higher propensity to migrate. In contrast, Borjas (1987) argues that migration is shaped by income inequality both at origin and destination. If income is distributed more unequally (equally) in the origin than in the destination, a negative (positive) selection of migrants is expected. This approach, requires a number of additional assumptions—most importantly, that migrants are not only well-informed about their position in the origin, but also about their future position in the destination. While the first assumption can be argued to be a result of social interaction between individuals in the same neighbourhood, the second depends on the available amount of information. Since the substitution of a reference group is additionally assumed to need a longer period of time (Stark and Taylor, 1991), especially the comparison with other individuals in the same region (i.e. in the origin) attracts notice.

In this paper we thus follow the approach of Stark (2006), by assuming that a higher RD at the origin might lead to a larger flow of emigrants, holding all other factors constant. We therefore test whether relative deprivation leads to a general ill-being that results in emigration. This effect is assumed to be independent of the destination, since the effective destination RD is assumed to be unknown.

2 Literature Overview

A number of previous studies have targeted this task from various perspectives and using different levels of spatial aggregation. For example, Stark, Micevska, and Mycielski (2009) use Polish regional data from 1999 to 2005 based on records of municipal population to test the impact of aggregate RD in communities on their emigration flows. By using a panel fixed effects model, they provide a robust relationship between higher income inequality and higher international as well as interregional emigration flows. Thus, higher levels of income inequality lead *ceteris paribus* to stronger migration propensities. A different perspective is provided by Czaika and de Haas (2012), who use data from the *Global Migration Origin Database* for 2000 to explore the impact of international RD on international migration. They present evidence that internal (within-country) RD affects emigration flows negatively for relatively income-poor individuals, while there is no effect for income-rich individuals. In a similar vein, Borjas (1987) shows evidence that countries with higher income inequality are suspect to lower emigration rates by investigating international emigration flows to the US from 41 different countries using census data. Liebig and Sousa-Poza (2004) use individual data for 23 countries to show that higher income inequality

tends to foster emigration rates, however higher skilled individuals are generally more prone to migrate.

A number of studies have focused on Mexico and its relations to the US: Quinn (2006) use cross-sectional data to analyse migration flows from Mexico to the US as well as internal migration within Mexico. He finds evidence that RD is a push factor especially in case of internal migration. Likewise, Stark and Taylor (1991) employ data from a survey of rural Mexican households to test the effect of RD on migration within Mexico as well as to the United States. However, their results indicate “income neutrality” (in terms of absolute and relative income) for internal migration, whereas they find support for the relative income hypothesis for the case of migration from Mexico to the US. In contrast, Aguayo-Téllez and Martínez-Navarro (2013) provide evidence for internal migration due to wage differences in Mexico.

In addition, Bhandari (2004) explores the differential access to cultivated land in an agricultural society in Nepal. By employing a household dataset, his results emphasise the importance of *relative land deprivation* as a determinant of migration. Jagger, Shively, and Arinaitwe (2012) present evidence that RD represents a main factor for circular migration in Uganda, based on household data of 2008. Furthermore, Hyll and Schneider (2014) explore the aversion of individual RD in the German Democratic Republic in 1990 and show that it influences the propensity to migrate in a positive way. Czaika (2012) analyses the impact of RD on migration of Indian individuals in 2008 and distinguishes between individual and collective RD. He defines RD based on inter-personal (individual RD) as well as inter-group (collective RD) comparisons, where the former is assumed to occur only within a certain group and not within the total population of a country. Reference groups are defined on the federal state level, by social class and religion. The author finds significant results for a positive impact of both types of RD on migration for all different groups and combinations thereof. Specifically, the results point to a strong impact on short-distance migration within a federal state.

In a very interesting contribution Kronenberg and Kronenberg (2011) examine the effect of RD on job mobility using data on Dutch employees of 10,864 regions. They consider three different reference groups based on the same neighbourhood, same employer and persons who share specific demographic characteristics. Their findings suggest that employees do indeed compare themselves to their geographic neighbours, rather than to their co-workers or people with similar characteristics. Similarly, Luttmer (2005) shows that individual (self-reported) life satisfaction is positively associated with the own income, however negatively associated with the regional average income. With respect to the classification of the reference group, Clark, Westergård-Nielsen, and Kristensen (2009) point to the role of small neighbourhoods by using Danish register data. The place and location therefore play an influential role for social processes (Tranmer et al., 2005).

While these results of empirical studies are not unambiguous, they indicate the essential role of disaggregated regional data. For example, Stark and Wang (2000) theoretically model migration as a response to relative deprivation and analyse whether a steady state can be reached, in which RD does not induce further migration. Their findings suggest that even though such an equilibrium does not exist independently of the initial income distribution, relative deprivation might still result in spatial segregation. Individuals and households tend to migrate towards similar social groups and live with these groups together (Simpson, 2007). In this vein, Rey (2004) points to the inter-correlation between income inequality, social tensions, and the spatial concentration of social groups. Furthermore Banzhaf and Walsh (2008) find evidence for spatial segregation through the housing market, where poorer households are crowded out by richer households due to the appreciation of local housing. For the case of Austria Moser and Schnetzer (2015) also find spatial patterns not only for income but also inequality. Accordingly, it seems imperative to include this small-scale spatial evidence in an analysis of inequality and migration.

This paper contributes to the existing literature on the nexus between income inequality as well as RD and internal migration. Our dataset enables us to employ the full population of a country and examine small neighbourhoods (i.e. within municipalities) in this regard. Most importantly, this microdata-focused approach allows for a direct identification of social groups that are more sensible to inequality and RD.

3 Data and Descriptives

In this analysis we use register data that cover Austrian municipalities and the 23 districts of Vienna for 2011 and 2012. The dataset comprises the total resident population of Austria being 16 years and older, and is based on data from the Austrian register-based census which has been enriched with income information from income tax registers. Overall, the dataset provides information on 7,174,250 individuals for 2011 and 7,231,925 for 2012, which can be attributed to 2347 geographical units. Due to Statistics Austria’s disclosure control the effective number of available municipalities for empirical analyses varies. This especially affects small municipalities in the West, which are subject to local suppression to minimize individual reidentification risk. The data set further provides individual information on types of gross, taxable, and net income, labour status as well as other socio-economic as well as demographic characteristics.

In the following we especially use total net income, which is defined as the sum of wage and self-employment income less taxes and social security benefits. This income definition includes supplementary payments, which, for Austria, constitute roughly on sixth of the regular yearly wage. Due to tax legislation changes we do not observe capital income, which is therefore not included. All calculations are based on the equivalized total net income, applying the OECD equivalence scale. We further exclude the top 2% income earners from each municipality to robustify our analysis with regard to extreme income outliers. It can be argued that these high-income earners do not participate in the local social life and are therefore not part of the relevant reference groups.

Moreover, we calculate emigration rates for each municipality as well as the 23 districts of the capital Vienna, $emi_{r,t}$, as the number of persons leaving municipality r within the next time period (from t to $t + 1$) relative to the total population of r in t . We exclude the persons aged 16 to 25 in order to mitigate the impacts of population movements for educational purposes (mainly students). In total we observe 190,093 movements from 2011 to 2012 and 182,022 movements from 2012 to 2013 of individuals who are older than 25.

Following Yitzhaki (1979) and Stark (1984) we define individual relative deprivation as the excess income normalized by the size of the population in the reference group. Formally, this can be represented as

$$RD_{i,r} = \frac{1}{n_r} \sum_{j=i+1}^{n_r} (x_j - x_i) \quad (1)$$

where $i = (1, \dots, n_r)$ is an individual in the total reference population in municipality r , and individuals are sorted by their income level x in ascending order. Based on this individual RD, we can calculate the average RD by municipality/reference group as,

$$RD_r = \frac{1}{n_r} \sum_{i=1}^{n_r} RD_{i,r} \quad (2)$$

Figure 1 provides a first visual impression of these average RD rates for Austrian municipalities. Since RD is a mean income-scaled version of the Gini (Yitzhaki, 1979), these results closely

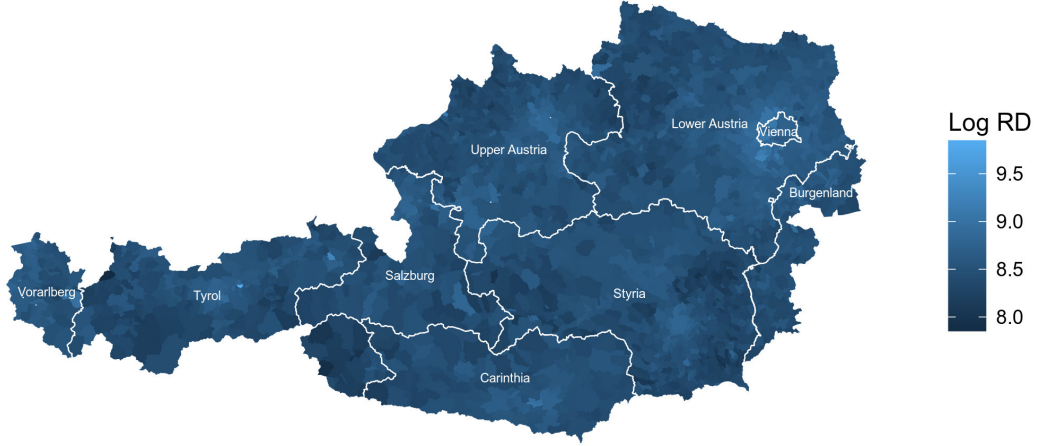


Figure 1: Mean Relative Deprivation for Austrian Municipalities, 2011

follow the original Gini-values calculated by Moser and Schnetzer (2015). Especially urbanized regions, such as the district capitals show above average values of RD—in the South this is visible for Klagenfurt (Carinthia) and Graz (Styria), as well as for Vienna (North-West). For the region surrounding Vienna, RD values continue to show high levels in the South, a suburbanized region that has gained popularity among residents. This trend is resembled by migration rates, housing prices as well as local infrastructure investments.

On the contrary, less developed regions at the Northern border but also West of Carinthia (Eastern Tyrol) show lower levels of RD. The two municipalities with the highest RD, apart from Vienna’s exclusive first district, can be found by visual inspection alone in Tyrol. These two communities are closely related to skiing tourism and an internationally well-known jewelry manufacturing industry.

Table 1 shows descriptive statistics for emigration rates (in %), average RD and median equivalised household income for Austrian federal states.

In general, all three variables are relatively stable over the two years. The emigration rates tend on average to decrease slightly in all provinces, whereas relative deprivation as well as absolute income increase during the same time. One exception is the capital, Vienna, where we find on average lower median equivalised household income, but higher relative deprivation in 2012 compared to 2011. Contrary to the relative deprivation measure, median income is robust to especially high incomes.

The highest emigration rates can be found in Vienna, which reflects a notable urban-rural contrast, insofar as the urban population seems to be more mobile. Interestingly, municipalities in Vorarlberg, the western-most province of Austria, depict the second highest average emigration rate. Likewise, we observe on average the highest income inequality in Vienna, again, followed by Vorarlberg, and Lower Austria. The low standard deviation of income inequality across municipalities in Vorarlberg implies that the high level of RD is distributed rather constantly across

Table 1: Descriptive statistics for municipalities by Austrian provinces¹

	<i>Emigration Rate (in %)</i>				<i>Average RD</i>				<i>Median Equiv. Income</i>			
	Min	Mean	Max	SD	Min	Mean	Max	SD	Min	Mean	Max	SD
Burgenland												
2011	0.75	2.04	7.81	0.77	3,245	4,114	5,866	443	7,151	9,110	11,720	959
2012	0.53	1.93	4.44	0.73	3,393	4,240	6,033	454	7,306	9,432	12,111	974
Carinthia												
2011	0.88	2.10	4.23	0.67	2,964	4,082	6,481	506	4,327	8,257	11,237	1,253
2012	0.55	1.98	3.80	0.56	3,039	4,184	6,560	515	4,713	8,532	11,441	1,234
Lower Austria												
2011	0.64	2.12	5.36	0.73	2,978	4,428	7,580	671	4,746	9,522	13,078	1,524
2012	0.62	2.06	9.22	0.75	3,083	4,548	7,990	686	4,972	9,805	13,621	1,519
Upper Austria												
2011	0.65	2.09	6.16	0.71	3,061	4,128	6,409	507	4,237	8,815	13,373	1,313
2012	0.64	2.00	5.53	0.67	3,166	4,253	6,535	516	4,397	9,099	13,741	1,332
Salzburg												
2011	0.83	2.24	4.41	0.73	2,931	4,148	5,637	584	4,829	8,560	10,775	1,176
2012	0.78	2.12	4.90	0.74	3,136	4,266	5,810	588	5,263	8,804	11,175	1,165
Styria												
2011	0.74	2.34	9.19	0.84	2,434	3,895	5,599	563	4,244	8,160	12,008	1,618
2012	0.00	2.23	14.76	0.97	2,519	4,001	5,825	569	1,910	8,430	12,288	1,667
Tyrol												
2011	0.00	2.19	6.54	0.85	2,427	4,021	6,110	611	1,979	8,046	13,667	1,429
2012	0.00	2.06	7.57	0.82	2,409	4,147	6,201	616	1,306	8,284	12,860	1,466
Vorarlberg												
2011	0.91	2.64	5.64	0.78	3,270	4,521	5,631	480	4,754	8,503	10,764	1,174
2012	0.00	2.41	4.33	0.75	3,415	4,664	5,870	496	4,757	8,745	11,129	1,195
Vienna												
2011	2.41	4.90	6.70	1.29	4,886	6,018	8,702	950	8,189	10,013	12,923	1,082
2012	2.24	4.61	6.11	1.17	4,956	6,122	8,787	950	7,970	9,914	13,018	1,194

¹Numbers are based on the population aged 16 and older. For emigration rates only people over 25 are considered. RD, relative deprivation; SD, standard deviation. Austrian Income Tax Register, 2011-2012.

municipalities. In contrast, Styria exhibits on average the lowest income inequality, but at the same time features a high dispersion in inequality across municipalities, indicated by the standard deviation. The absolute income reveals a similar pattern, which means that municipalities with higher absolute income are simultaneously characterised by higher income inequality (Moser and Schnetzer, 2015). Thus, Table 1 emphasises regional heterogeneity not only across Austrian provinces, but also across municipalities in the respective federal states.

Figure 2 provides a first insight into the relationship between average RD within Austrian municipalities including the Viennese districts, and its emigration flows. The vertical axis is assigned to the means of (log) emigration rates between 2011 and 2012, whereas the horizontal axis corresponds to the means of the (log) average RD between 2011 and 2012. The graphs are separated by federal states to emphasise potential heterogeneity. In addition, we assign urbanisation classifications to each municipality by distinguishing thinly populated areas (rural areas), intermediate density area (towns and suburbs) and densely populated area (urban centres). In general, Figure 2 depicts a positive correlation between emigration rates and our income inequality measure. Moreover, we can discover a common urbanisation pattern across federal states. Accordingly, rural areas tend to be characterised by a lower relative deprivation and lower emigration rates. In contrast, intermediate and urban areas tend to exhibit higher values for both variables. For the following econometric analysis we need to take this urbanisation clustering into account, since emigration rates are influenced by these alongside other characteristics. The role of urbanisation structures for migration is also addressed by Congdon (2010). Figures 4 and 5 in the Appendix present the relationship between emigration rate and median equivalised household income, as well as between median equivalised household income and average relative deprivation. In Figure 5 we find a positive relationship between median income and income inequality. This correlation is in line with the argument, that a higher income level generally results in a higher income inequality and thus average relative deprivation.

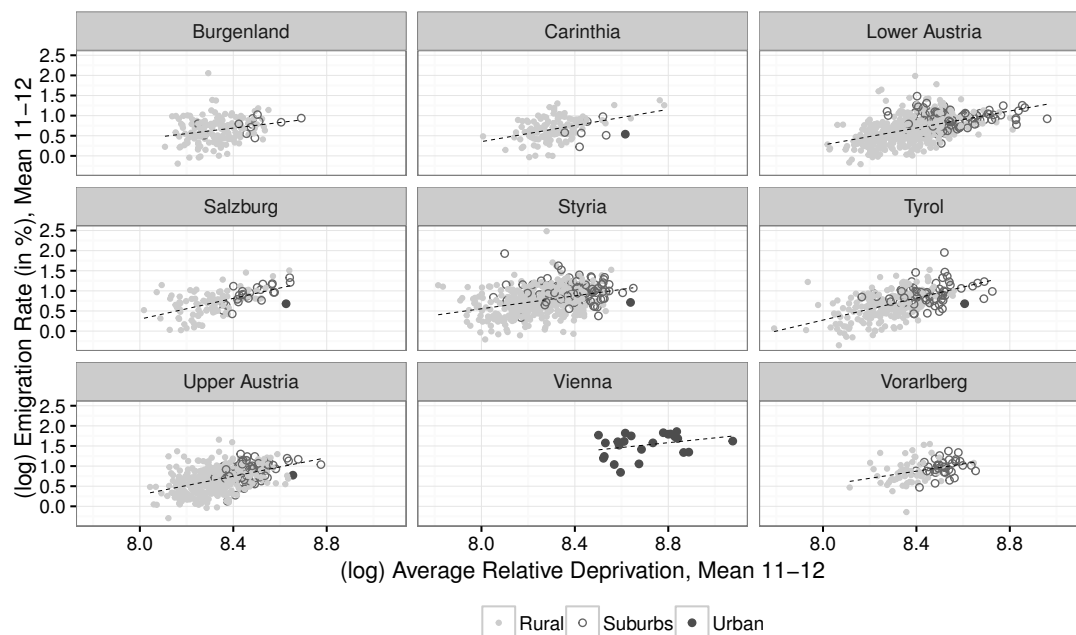


Figure 2: Emigration rate and relative deprivation, means 2011-2012, Wage and income tax data

4 Empirical Framework

The social psychologist Runciman (1966) formulated an early notion of the concept of relative deprivation when he considers an individual as “*relatively deprived of X when (i) he does not have X , (ii) he sees some other person or persons (possibly including himself at some previous or future time) as having X , (iii) he wants X , and (iv) he sees it as feasible that he should have X* ”. Based on this concept, individuals do not only derive utility from their own income, but also from their relative position in the income distribution of a reference group. Stark (1984) and Stark and Taylor (1989) measure the degree of an individual’s relative deprivation by multiplying the mean excess income by the share of individuals in the reference group that earn a higher income, and relate this measure to the migration behaviour of individuals. Under the presumption that individuals have a dis-taste for relative deprivation, they might not only migrate in order to achieve a higher absolute income, but also to improve their relative position in the income distribution. Following these early contributions, we proceed with considering relative deprivation as a push factor for emigration rates of Austrian municipalities. In a first step, we examine the general relationship between emigration flows and income inequality and derive the following hypothesis:

Hypothesis 1: “*An increase in relative deprivation in a municipality causes higher emigration rates, ceteris paribus.*”

To empirically test this hypothesis we consider the overall income inequality within municipalities and determine its impact on the total outflow of persons, i.e. on internal migration to other Austrian municipalities. More formally, we want to estimate a model of the form,

$$emi_{r,t} = \alpha + \beta RD_{r,t} + \gamma Y_{r,t} + \mathbf{X}_{r,t}\boldsymbol{\delta} + \mu_d + \xi_t + \eta_u + u_{r,t}, \quad (3)$$

where $RD_{r,t}$ is the (log) average RD in municipality r at time t , computed as the arithmetic mean of all individual RDs in the municipality. $Y_{r,t}$ is the (log) absolute income level in r at t , \mathbf{X} denotes a vector of municipality-specific control variables and $u_{r,t}$ is the remaining error, which is assumed to be i.i.d. In addition, μ_d captures district, ξ_t time and η_u urbanisation fixed effects. (Theoretically, the implementation of municipality fixed effects would be feasible because we observe two time periods, 2011 and 2012. Due to the considerable persistence in the data, however, we refrain from using municipality fixed effects and use district fixed effects instead. Moreover, in a model with only two periods, panel fixed effect estimations lead algebraically to the same results as first differencing – see also Angrist and Pischke (2008).) \mathbf{X} comprises sociodemographic information, including the total population of the municipality as well as shares of educational attainment and age groups, household structure measures, unemployment and poverty rates for each municipalities at time t .

We use average relative deprivation as defined in equation 2, and introduced by Stark (1984) next to Stark and Taylor (1991). The reference group is defined as the total population in a given municipality r . Following the theoretical arguments in the related literature, average RD in model 3 is expected to exhibit a positive impact, indicating increased emigration rates as a response to higher income inequality. Municipalities that are characterised by higher average RD are thus likely to exhibit higher emigration rates, *ceteris paribus*. Although individuals with lower levels of income and education tend to be more relatively deprived, absolute deprivation in the form of absolute income poverty might constrain the migration aspirations of these individuals.

The inclusion of the absolute income level and a measure of poverty (share of persons with income below 60% of median income in a municipality) of municipalities on top of the relative income measures enables us to control for these potential constraints.

By contrast, individuals with higher income and higher educational attainment exhibit larger levels of human capital and have an easier access to technologies, whereby they can assess employment and livelihood opportunities in a more advanced way (Czaika and de Haas, 2012). To capture the role of human capital, we control for the educational attainment within municipalities, expecting in general positive effects of human capital on emigration rates. The absolute income captures to a certain extent the general welfare level of a regional unit. Thus, it can also be regarded as an indicator for a region’s infrastructural endowment (e.g. health, education) and additionally for the general price level of housing and real estate. Individuals in regions with lower income levels might exhibit a higher propensity to migrate, because they want to have access to better infrastructure. Furthermore, we include the average number of household members (without children), and children within a regional unit to consider the household structure, which might also influence the decision to migrate. In order to approximate regional job availability and opportunities, we include unemployment rates on the municipality level to our model. Moreover, we might expect different impacts on emigration over the life-cycle of individuals, wherefore we control for the age distribution within municipalities. To control for the degree of urbanisation we further include the (log) population of each municipality.

In the general specification above, we do not allow for heterogeneous effects across different subgroups of the population, and therefore the conclusion that those individuals migrate that face the highest levels of RD is not yet justified. As individuals allocated at the bottom of the income distribution are confronted with the highest levels of RD, they should react particularly strong to distributional changes (see for instance Stark, 2006). Accordingly, we explore whether the average RD has a stronger impact on the emigration rates of specific subgroups within municipalities and state hypothesis 2:

Hypothesis 2: *“Income inequality has a stronger positive impact on the propensity to emigrate of individuals at the lower part of the income distribution, individuals with lower education, and individuals of working age.”*

As educational attainment is generally positively correlated with income, the impact of changes in average RD should be more pronounced among low skilled individuals. If their low education levels are reflected in lower incomes, their individual RD is disproportionately affected by increases in overall RD in the municipality. Also with respect to broad age groups, effect heterogeneity is likely. Although it is generally more likely that younger people migrate, they might react less sensible to relative deprivation or tend to exhibit a higher acceptance for relative deprivation when they believe in social mobility. Since they might be just at the start of their careers and expect to climb up the career ladder, they could similarly be less affected by RD. Compared to younger people, middle aged people are assumed to react stronger to changes in RD. On the contrary, older people are regarded to be less sensible to relative deprivation, since they are less mobile in general and might have stronger ties to their place of residence.

In order to capture this heterogeneity across different socio-economic groups, we examine the impact of changes in average RD on the emigration rates of subgroups based on income, education as well as age. The subgroups are indicated by $q = 1, \dots, Q$. RD represents again the average over all individual RDs in a specific municipality, where the reference group is still the total population within a municipality. We apply the following model specification,

$$emi_{r,t}^q = \alpha + \beta RD_{r,t} + \gamma Y_{r,t} + \mathbf{X}_{r,t}\boldsymbol{\delta} + \mu_d + \xi_t + \eta_u + u_{r,t}, \quad (4)$$

where $emi_{r,t}^q$ is the (log) emigration rate of subgroup q in municipality r in district d at time t (leaving within the next period). Since we control for poverty rates—a proxy for absolute deprivation—as well as for human capital, we expect a higher positive effect of RD on emigration rates of individuals with low levels of income and educational attainment. Individuals who are located at lower parts of the income distribution face higher levels of RD, and that implies *ceteris paribus* a higher marginal propensity to migrate for these groups. Likewise, lower educated individuals are assumed to reveal higher positive impacts emanating from a higher RD. Furthermore, we hypothesise a higher positive impact of relative deprivation for middle-aged individuals especially compared to older ones.

5 Results

Our dataset provides information on each municipality and the districts' capitals for the years 2011 and 2012. While the raw numbers are available for all 2347 geographical units, a small number of missing values are included, due to data transformation as well as data anonymisation requirements.

For the estimation of the empirical model described in section 4, we employ a pooled cross sectional regression model framework. In order to control for unobserved regional and time heterogeneity, we implement time, district and urbanisation fixed effects. All models are estimated using least squares optimization including robust standard errors. Simultaneity issues might arise from a possible feedback of emigration on income inequality. Since migration rates are low compared to the total population, the inequality measures are expected to be rather robust. Nevertheless to effectively mitigate these minor simultaneity issue, we use lagged inequality measures, that are not affected by subsequent emigration.

Recalling our first hypothesis, we want to test the general impact of average RD on the total outflows of municipalities to other Austrian municipalities. Section 4 already indicated a list of possible covariates, which might additionally influence emigration decisions, and hypothesised about the sign of their effect. In order to assess the sensibility of the estimated RD coefficient, we enlarge the parsimonious initial model successively by adding other explanatory variables. Since municipalities can vary substantially in terms of population and area, we include, alongside average RD, population density in each specification. In the following, we extend the model by adding absolute income (2), household structure variables (3), poverty rate (4), unemployment rate (5), age structure variables (6), and educational attainment (7).

Table 2 presents the results for all seven specifications. In line with the theoretical reasoning, we find positive and significant estimates for average RD in all specifications. A higher relative deprivation—and thus higher level of income inequality—in a municipality leads to a higher overall outflow from this municipality, *ceteris paribus*. This relationship still prevails if we control additionally for absolute income levels. Contrary to relative deprivation, the impact of absolute income exhibits unstable results, but tends to influence emigration rates negatively. Theoretically it is argued, that higher income levels are correlated with the availability of a more developed infrastructure, and thus, lower the incentives to move to another municipality. This result is also empirically well established, but mostly in cross-country studies. Especially for Austria, absolute income levels are more homogenous than in other countries and cross-country perspectives, so that it can be argued that absolute income is less important as a push factor for emigration.

Furthermore, the population density proxy indicates that more densely populated municipalities tend to reveal lower emigration rates. This is most likely an effect of the ongoing rural depopulation process in Austria (i.e. more internal movements from rural to (sub-)urban municipalities). The two household structure variables additionally emphasise the importance of household size: For larger families, moving to another municipality is much more difficult than it is for smaller ones. Contrary to that, the poverty rate is found to not contribute significantly to the explanation of emigration flows. Despite this finding, unemployment rates show a significantly positive impact on internal emigration flows. Since unemployment represents a proxy for job opportunities, higher unemployment rates, and thus lower job opportunities, increase the mobility of locals. The included variables on age structure provide evidence for a change in the propensity to emigrate over the life-cycle, insofar as younger cohorts show higher emigration propensities. Furthermore, high education levels increase emigration propensities compared to regions with lower average education. This finding might resemble the difference in job markets for different education levels. While persons with A-level education might find a secure job in their own region, highly educated individuals might (need to) embrace job opportunities in other regions.

Since Austria is characterised by differently sized municipalities (see Figure 1), we might expect varying impacts of relative deprivation depending on the size of the municipality, measured by the total head count. In order to test this relationship, we rerun the previous specifications including an interaction term between RD and total population. Table 4 presents the results of this extension, i.e. including the interaction term as an additional explanatory variable. Overall, the results closely resemble those of the previous setup in Table 2. However, the positive sign of the interaction term suggests a stronger effect of RD in larger municipalities. A possible underlying explanation could be that social ties in rural areas are stronger, whereas in larger urban areas comparisons between individuals might rest to some degree upon conspicuous consumption and relative deprivation becomes more influential.

A rare example for this effect is provided by Stark, Micevska, and Mycielski (2009), who find no robust effects of absolute income levels on emigration from Polish regions.

These results so far highlight the role of the overall income inequality as a push factor for emigration decisions in Austrian rural and especially in urbanized municipalities. The comparison to other persons in the direct neighbourhood thus has an influence on the propensity to emigrate and even prevails if we control for other covariates, such as absolute income levels. Interestingly, the absolute income level of a municipality has a considerably lower impact compared to the relative income level (i.e. RD).

In a further step we address the second hypothesis of this paper: We expect heterogeneity in the impact of average RD across social groups. Accordingly, we estimate the specification separately for different subgroups. While there may be a number of different social groups, we focus on those common in the literature, which are especially stratified by education, household income and age. This approach enables us to identify subgroups that react more sensible to relative deprivation compared to other groups. To test these effects, we re-estimate the complete regression model (i.e. model (7) in Table 2), but replace overall emigration rates by subgroup-specific emigration rates as the dependent variable.

Figure 3 plots the estimated coefficients of the overall income inequality on the emigration rates of the defined subgroups. The whiskers indicate the 95% confidence interval. Detailed results of the corresponding models are presented in the Appendix.

In general, education is assumed to be positively correlated with income, so that less educated persons are more likely to face higher relative deprivation. Figure 3c presents coefficient estimates of the RD effect on education specific emigration rates. The findings suggest that RD influences only the emigration of individuals with low and medium levels of education, whereas

Table 2: Pooled cross-sectional regression model, 2011-2012¹

<i>Dependent variable:</i>	<i>emigration rate, in % (log)</i>						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Avg RD (log)</i>	1.282*** (0.0538)	1.277*** (0.119)	1.140*** (0.107)	1.216*** (0.129)	1.234*** (0.134)	1.285*** (0.118)	1.170*** (0.154)
<i>Median Income (log)</i>		0.00439 (0.118)	-0.251** (0.127)	-0.345** (0.158)	-0.279 (0.175)	-0.283** (0.141)	-0.267* (0.141)
<i>Total Pop. in 1000 (log)</i>	-0.114*** (0.00806)	-0.114*** (0.00826)	-0.116*** (0.00810)	-0.116*** (0.00813)	-0.114*** (0.00836)	-0.117*** (0.00830)	-0.122*** (0.00851)
<i>Number of Children</i>			-0.169 (0.109)	-0.176 (0.110)	-0.153 (0.111)	-1.219*** (0.153)	-1.267*** (0.152)
<i>Number of HH-members</i>			-0.301*** (0.0524)	-0.302*** (0.0525)	-0.253*** (0.0595)	-0.108* (0.0581)	-0.109* (0.0587)
<i>Poverty Rate</i>				-0.00618 (0.00449)	-0.00287 (0.00465)	0.00125 (0.00428)	0.000480 (0.00426)
<i>Unemployment Rate</i>					0.0117*** (0.00299)	0.0115*** (0.00289)	0.0120*** (0.00289)
<i>Aged 26-39 (in %)</i>						0.0264*** (0.00434)	0.0267*** (0.00438)
<i>Aged 40-64 (in %)</i>						-0.00691* (0.00398)	-0.00764* (0.00406)
<i>Older than 64 (in %)</i>						-0.0134*** (0.00330)	-0.0147*** (0.00329)
<i>Apprenticeship (in %)</i>							-0.000619 (0.00225)
<i>A-levels (in %)</i>							-0.00814*** (0.00226)
<i>Higher Edu (in %)</i>							0.0123*** (0.00322)
<i>Constant</i>	-10.04*** (0.457)	-10.05*** (0.484)	-5.840*** (0.817)	-5.420*** (0.916)	-6.453*** (1.058)	-7.033*** (0.959)	-5.982*** (1.094)
Observations	4,566	4,566	4,566	4,566	4,480	4,480	4,475
Adjusted R-squared	0.337	0.337	0.347	0.347	0.354	0.385	0.391

¹Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. In the pooled cross-section we use time-, district- and urbanisation-fixed effects (the latter according to *Statistik Austria*). Results of the fixed effects are not shown. *A-level* comprises *BMS*, *AHS* and *BHS*. *Higher Edu* contains *Kollege*, *Hochschule* and *Uni/Fachhochschule*. *People between 17-25 (in %)* and *people with compulsory or less education (in %)* represent basegroup. RD, relative deprivation; HH, household; Avg, average.

highly skilled individuals appear not to react to changes in RD. Due to better earning opportunities, highly educated individuals tend to exhibit a lower level of relative deprivation, which might result in RD being an irrelevant determinant of emigration. In addition, highly educated individuals are more likely to substitute their reference groups faster than others (Czaika and de Haas, 2012). Although the movements just occur in the next period, such individuals might already compare with a reference group in another municipality.

Instead of using education groups as a proxy for income, the dataset allows us to directly assess the impact of RD on emigration across income groups. This extension is of particular importance, as it can support the presumption that individuals that do migrate are indeed those who face the highest levels of RD. Figure 3b shows this effect for five income quintiles. We find these to be similar to the results for education groups and generally conclude that individuals with lower income react more sensitive to changes in income inequality than individuals with higher income. An exception are individuals located in the second quintile of the income distribution, which is the part of the distribution with the lowest overall emigration rates. Explanations for this finding are not unambiguous, but might indicate that these below average income groups feature a higher local connectivity. Moreover, RD does not seem to be a push factor for the highest income groups, similar to the highly educated. This result is line with our hypotheses, since RD as a measure concentrates on the respective right-side of the income distribution. Only few individuals have a higher income than those in the top quintile, and for that reason, RD for this group is comparably low.

Analysing age cohorts in Figure 3a, we discover a strong and positive impact of RD on the emigration rates of individuals aged 26 up to 64. Unsurprisingly, individuals in the age of the retirement depict a reversed impact. Typical explanations for this reversed relationship might be that retirees receive and will receive only a constant income stream in the future (assuming that they only receive pensions). Therefore, their reference group may differ from the working population resulting in less social status comparisons. Our results shed light on the heterogeneous impact of income inequality (Figures 3b and 3c) across social groups within municipalities. In general, lower educated and lower income individuals are more sensible to relative deprivation compared to highly educated, rich individuals. Furthermore, individuals in the working age seem to be more sensitive to distributional changes. In contrast, old-age individuals appear to appreciate or at least tolerate high levels of relative deprivation.

5.1 Further Robustness Checks

In order to verify the robustness of the results presented above, we conduct additional robustness checks. First, we rerun all regressions by using the mean values for all variables. To mitigate the potential impact of outliers, we calculate mean values over 2011 and 2012 to smooth values. By applying mean values in our regression models, we obtain coinciding results. The relative deprivation measure is consistent with the results above.

Since we use small-scale regional data, it is likely that there exist interdependencies between different municipalities (see for instance Congdon (2010) for spatial dependency in analysing migration flows). Smith, Raymer, and Giulletti (2010) point to spatial patterns of internal migration in England. Therefore, we shall incorporate a spatial dimension in our regression framework. The detection of spatial dependency and the choice of the appropriate spatial econometric model depends substantially on the definition of the so-called spatial weight (W) matrix. Due to this fact, we generate two different spatial weight matrices, based on *distance* and on the *k-nearest neighbours*, respectively. We calculate Moran's I to test for spatial dependency in our model. The test statistics indicate that spatial autocorrelation persists. Further test statistics

Table 3: Spatial regression models, means 2011-2012¹

<i>Dependent variable:</i>	<i>emigration rate, in % (log)</i>	
<i>Model:</i>	Spatial error model	Spatial autoregressive model
<i>W-matrix:</i>	Distance-based (40km)	KNN4
<i>Avg RD (log)</i>	1.244*** (0.131)	1.145*** (0.121)
<i>Median income (log)</i>	-0.283*** (0.101)	-0.391*** (0.098)
<i>Total pop. in 1000 (log)</i>	-0.110*** (0.007)	-0.099*** (0.007)
<i>Number of children</i>	-1.397*** (0.123)	-1.416*** (0.115)
<i>Number of HH-members</i>	-0.129** (0.056)	-0.041 (0.051)
<i>Poverty rate</i>	0.002 (0.004)	-0.004 (0.004)
<i>Unemployment rate</i>	0.014*** (0.003)	0.005** (0.002)
<i>Aged 26-39 (in %)</i>	0.022*** (0.004)	0.024*** (0.004)
<i>Aged 40-64 (in %)</i>	-0.015*** (0.004)	-0.008** (0.003)
<i>Older than 64 (in %)</i>	-0.023*** (0.003)	-0.014*** (0.003)
<i>Apprenticeship (in %)</i>	0.0003 (0.002)	0.003** (0.002)
<i>A-level (in %)</i>	-0.010*** (0.002)	-0.013*** (0.002)
<i>Higher edu (in %)</i>	0.015*** (0.003)	0.016*** (0.003)
<i>Constant</i>	-4.926*** (0.987)	-3.892*** (0.859)
λ	0.867*** (0.038)	- (-)
ρ	- (-)	0.291*** (0.022)
Observations	2,303	2,303
AIC	34.104	61.465

¹Regressions based on average values. Estimates generated by a Maximum Likelihood Estimation. * p<0.1, ** p<0.05, *** p<0.01. A-level comprises BMS, AHS and BHS. Postsecondary/tertiary contains Kollege, Hochschule and Uni/Fachhochschule. People between 17-25 (in %) and people with compulsory or less education (in %) represent basegroup. RD, relative deprivation; HH, household; Avg, average.

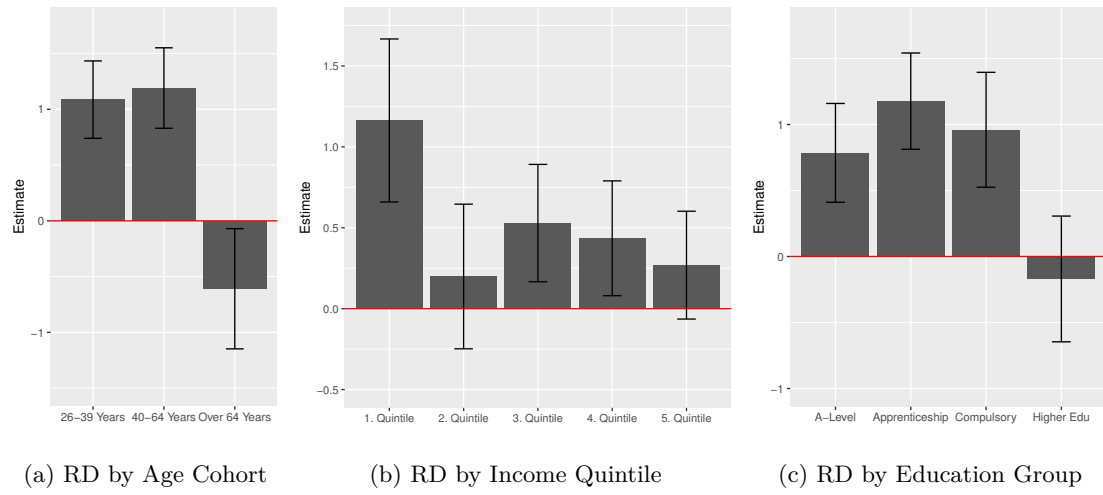


Figure 3: Impact of RD on emigration rates for different social groups. Bars indicate estimated coefficients, black whiskers mark the 95% confidence interval

Table 4: Pooled cross-sectional regression model with interaction, 2011-2012¹

<i>Dependent variable:</i>	<i>emigration rate, in % (log)</i>						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Avg RD (log)</i>	1.261*** (0.0541)	1.220*** (0.124)	1.083*** (0.111)	1.165*** (0.133)	1.192*** (0.138)	1.235*** (0.122)	1.191*** (0.154)
<i>Median Income (log)</i>		0.0431 (0.121)	-0.212 (0.131)	-0.312* (0.161)	-0.265 (0.177)	-0.272* (0.142)	-0.269* (0.141)
<i>Total Pop. in 1000 (log)</i>	-1.921*** (0.359)	-1.959*** (0.371)	-1.948*** (0.370)	-1.966*** (0.368)	-1.585*** (0.387)	-1.773*** (0.374)	-1.257*** (0.386)
<i>Total Pop. × Avg RD (log)</i>	0.216*** (0.0427)	0.220*** (0.0442)	0.219*** (0.0441)	0.221*** (0.0438)	0.176*** (0.0460)	0.198*** (0.0445)	0.135*** (0.0460)
<i>Number of Children</i>			-0.173 (0.108)	-0.181* (0.109)	-0.153 (0.110)	-1.228*** (0.153)	-1.257*** (0.152)
<i>Number of HH-members</i>			-0.298*** (0.0524)	-0.300*** (0.0525)	-0.257*** (0.0595)	-0.117** (0.0581)	-0.110* (0.0588)
<i>Poverty Rate</i>				-0.00669 (0.00445)	-0.00368 (0.00466)	0.000492 (0.00428)	-7.42e-05 (0.00426)
<i>Unemployment Rate</i>					0.0110*** (0.00300)	0.0106*** (0.00290)	0.0113*** (0.00291)
<i>Aged 26-39 (in %)</i>						0.0262*** (0.00432)	0.0266*** (0.00437)
<i>Aged 40-64 (in %)</i>						-0.00632 (0.00400)	-0.00700* (0.00408)
<i>Over 64 (in %)</i>						-0.0142*** (0.00329)	-0.0150*** (0.00329)
<i>Apprenticeship (in %)</i>							-0.000443 (0.00224)
<i>A-levels (in %)</i>							-0.00767*** (0.00226)
<i>Higher Edu (in %)</i>							0.00986*** (0.00335)
<i>Constant</i>	-10.01*** (0.454)	-10.05*** (0.481)	-5.859*** (0.820)	-5.405*** (0.920)	-6.283*** (1.064)	-6.785*** (0.966)	-6.207*** (1.096)
Observations	4,566	4,566	4,566	4,566	4,480	4,480	4,475
Adjusted R-squared	0.341	0.341	0.351	0.352	0.356	0.388	0.393

¹Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. In the pooled cross-section we use time-, district- and urbanisation-fixed effects (the latter according to *Statistik Austria*). A-level comprises *BMS*, *AHS* and *BHS*. Postsecondary/tertiary contains *Kollege*, *Hochschule* and *Uni/Fachhochschule*. People between 17-25 (in %) and people with compulsory or less education (in %) represent basegroup. RD, relative deprivation; HH, household; Avg, average.

suggest the choice of a spatial error model (by using the distance-based matrix) and a spatial lag model (by using the k-nearest neighbour matrix). Table 3 shows the results of the base model (see Table 2) by considering all explanatory variables and using mean values. The results of both spatial regressions are consistent with our main findings above. Another choice for the bounds in the spatial weight matrices (40 kilometres and 4 direct neighbours, respectively) changes the results only marginally. The main findings remain robust.

6 Conclusion

As been put forward by the literature on the *New Economics of Labour Migration*, relative deprivation plays an important role in shaping the migration behaviour of individuals. On top the aspiration to improve the absolute income, also changing the income relative to a reference group can constitute a motive for migration—among other important political, social or environmental factors. As empirical evidence for this relationship is scarce, we use unique data to assess empirically the link between relative deprivation and migration. Relying on register-based individual level data on income, socio-economic characteristics and the municipality of residence of the Austrian population we construct a two-period panel data set at the level of municipalities, that contains information on emigration rates of municipalities, alongside mean and median income, income dispersion and a series of socio-economic characteristics. Controlling for district fixed effects, and a set of covariates, we find that increases in relative deprivation in municipalities lead to higher emigration rates. Allowing further for heterogeneous effects of relative deprivation on migration of individuals belonging to different subgroups of the population, we find additional evidence for a response of individuals’ migration behaviour to changes in the dispersion of incomes. Emigration rates of individuals belonging to lower income quintiles react stronger to distributional changes, whereas emigration rates of individuals in the top income quintile do not appear to respond to a variation in income inequality. A similar pattern is found for education-specific emigration rates. Low and medium skilled individuals increase their propensity to migrate if income inequality increases, whereas emigration rates of high skilled individuals do not seem to change as a response to distributional changes. We further find that the relationship between income inequality and emigration holds for individuals of the working age, whereas older individuals do not tend to migrate more if income inequality increases.

Apart from contributing to our understanding of the migration behaviour of individuals, this piece of research specifically wants to contribute to the discussion of the implications of inequality. Migration decisions appear to depend, among a series of other factors, also on distributional changes, and widening income distributions could cause not only higher emigration rates, but also a change of the socio-economic profiles of emigrants. This is thus also a crucial factor in constructing policies that target social inequality: the individual’s sensitivity to local inequality needs to be considered when topics, such as *inclusive growth*, are addressed. In this regard, unequal gains from economic prosperity can extend impacts, e.g. on regional development, rural depopulation and manifest spatial segregation. Since low income groups do not only experience the vast amount of relative deprivation but have also been faced with sub-par income growth rates in the recent decade (Piketty and Saez, 2006), economically disadvantaged groups do not only fall behind the *Joneses*, but may increasingly break local, social ties as a response to these phenomena.

References

- Aguayo-Téllez, E. and J. Martínez-Navarro (2013): “Internal and International Migration in Mexico: 1995–2000”. In: *Applied Economics* 45.13, pp. 1647–1661.
- Angrist, J. D. and J.-S. Pischke (2008): *Mostly Harmless Econometrics: An Empiricist’s Companion*. Princeton University Press.
- Banzhaf, S. H. and R. P. Walsh (2008): “Do People Vote with Their Feet? An Empirical Test of Tiebout’s Mechanism”. In: *The American Economic Review* 98.3, pp. 843–863.
- Bhandari, P. (2004): “Relative Deprivation and Migration in an Agricultural Setting of Nepal”. In: *Population and Environment* 25.5, pp. 475–499.
- Borjas, G. (1987): “Self-selection and the earnings of immigrants.” In: *American Economic Review* 77.4, pp. 531–53.
- Clark, A. E., N. Westergård-Nielsen, and N. Kristensen (2009): “Economic Satisfaction and Income Rank in Small Neighbourhoods”. In: *Journal of the European Economic Association* 7.2-3, pp. 519–527.
- Congdon, P. (2010): “Random-effects models for migration attractivity and retentivity: a Bayesian methodology”. In: *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 173.4, pp. 755–774.
- Czaika, M. (2012): “Internal versus International Migration and the Role of Multiple Deprivation: Some Evidence from India”. In: *Asian Population Studies* 8.2, pp. 125–149.
- Czaika, M. and H. de Haas (2012): “The Role of Internal and International Relative Deprivation in Global Migration”. In: *Oxford Development Studies* 40.4, pp. 423–442.
- Duesenberry, J. S. (1949): “Income, Saving, and the Theory of Consumer Behavior”. In: *Harvard University Press*.
- Hyll, W. and L. Schneider (2014): “Relative deprivation and migration preferences”. In: *Economics Letters* 122.2, pp. 334–337.
- Jagger, P., G. Shively, and A. Arinaitwe (2012): “Circular migration, small-scale logging, and household livelihoods in Uganda”. In: *Population and Environment* 34.2, pp. 235–256.
- Kronenberg, K. and T. Kronenberg (2011): *Keeping up with the Joneses by Finding a Better-Paid Job-The Effect of Relative Income on Job Mobility*. Tech. rep. MPRA Paper No.29426.
- Liebig, T. and A. Sousa-Poza (2004): “Migration, Self-Selection and Income Inequality: An International Analysis”. In: *Kyklos* 57.1, pp. 125–146.
- Luttmer, E. F. (2005): “Neighbors as Negatives: Relative Earnings and Well-Being”. In: *The Quarterly Journal of Economics*, pp. 963–1002.
- Moser, M. and M. Schnetzer (2015): “The Income–Inequality Nexus in a Developed Country: Small-Scale Regional Evidence from Austria”. In: *Regional Studies*, pp. 1–13.
- Piketty, T. and E. Saez (2006): “The evolution of top incomes: a historical and international perspectives”. In: *American Economic Review Papers and Proceedings*. Vol. 96. 2, pp. 200–205.
- Quinn, M. A. (2006): “Relative Deprivation, Wage Differentials and Mexican Migration”. In: *Review of Development Economics* 10.1, pp. 135–153.

- Raymer, J., G. Abel, and P. W. Smith (2007): “Combining census and registration data to estimate detailed elderly migration flows in England and Wales”. In: *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 170.4, pp. 891–908.
- Rey, S. J. (2004): “Spatial Analysis of Regional Income Inequality”. In: *Spatially Integrated Social Science* 1, pp. 280–299.
- Runciman, W. G. (1966): “Relative Deprivation and Social Justice: Study Attitudes Social Inequality in 20th Century England”. In: *University of California Press*.
- Sen, A. (1976): “Poverty: an ordinal approach to measurement”. In: *Econometrica: Journal of the Econometric Society*, pp. 219–231.
- Simpson, L. (2007): “Ghettos of the mind: the empirical behaviour of indices of segregation and diversity”. In: *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 170.2, pp. 405–424.
- Smith, P. W., J. Raymer, and C. Giulletti (2010): “Combining available migration data in England to study economic activity flows over time”. In: *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 173.4, pp. 733–753.
- Stark, O. (1984): “Rural-to-Urban Migration in LDCs: A Relative Deprivation Approach”. In: *Economic Development and Cultural Change* 32.3, pp. 475–486.
- (2006): “Inequality and Migration: A Behavioral Link”. In: *Economics Letters* 91.1, pp. 146–152.
- Stark, O., M. Micevska, and J. Mycielski (2009): “Relative Poverty as a Determinant of Migration: Evidence from Poland”. In: *Economics Letters* 103.3, pp. 119–122.
- Stark, O. and J. E. Taylor (1989): “Relative Deprivation and International Migration”. In: *Demography* 26.1, pp. 1–14.
- (1991): “Migration Incentives, Migration Types: The Role of Relative Deprivation”. In: *The economic journal* 101.408, pp. 1163–1178.
- Stark, O. and Y. Q. Wang (2000): “A Theory of Migration as a Response to Relative Deprivation”. In: *German Economic Review* 1.2, pp. 131–143.
- Stark, O. (2017): “Migration when social preferences are ordinal: Steady state population distribution, and social welfare”. In: *Economica* (forthcoming).
- Stark, O. and D. E. Bloom (1985): “The New Economics of Labor Migration”. In: *The American Economic Review* 75.2, pp. 173–178.
- Tranmer, M. et al. (2005): “The case for small area microdata”. In: *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 168.1, pp. 29–49.
- Veblen, T. (1899): “The Theory Of the Leisure Class”. In: *New York: The New American Library*.
- Verme, P. (2013): *The Relative Income and Relative Deprivation Hypotheses: A Review of the Empirical Literature*. SSRN Scholarly Paper ID 2327362. Rochester, NY: Social Science Research Network. (Visited on 12/02/2016).
- Yitzhaki, S. (1979): “[Relative Deprivation and the Gini Coefficient](#)”. In: *The Quarterly Journal of Economics* 93.2, pp. 321–324. ISSN: 0033-5533. (Visited on 12/01/2016).

Appendix A: Relationships between main variables

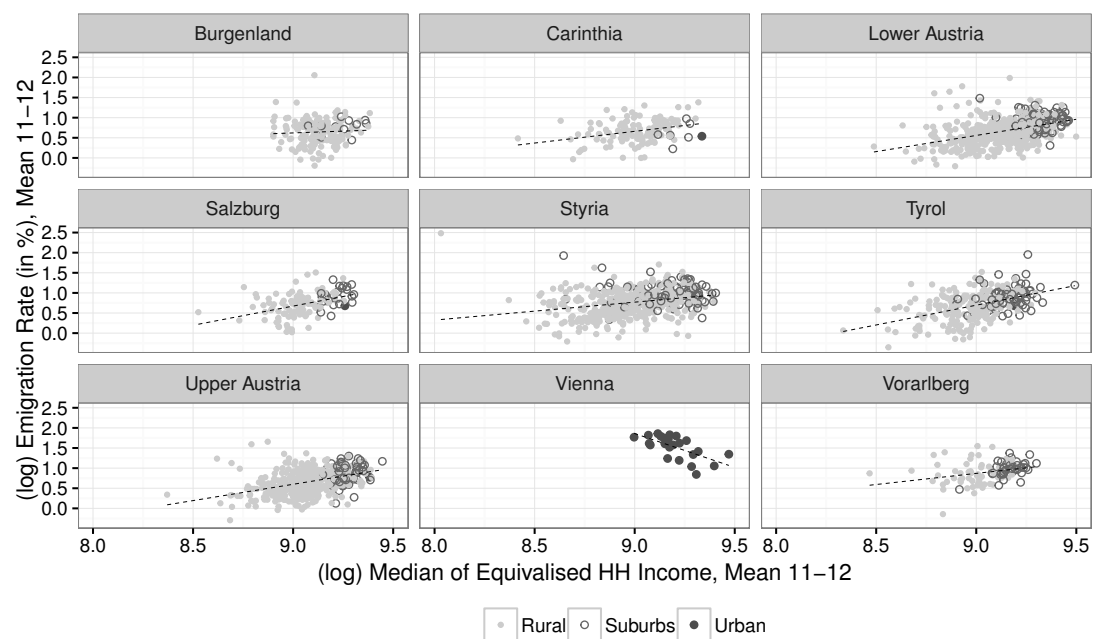


Figure 4: Emigration rate and median of equivalised household income, means 2011-2012, Wage and income tax data

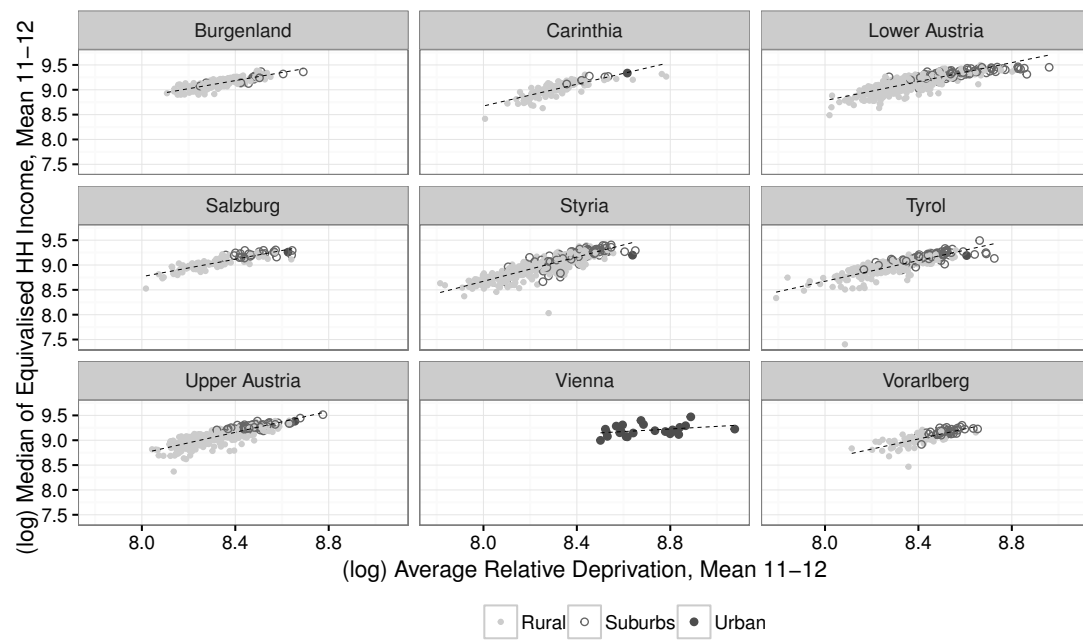


Figure 5: Median of equivalised household income and relative deprivation, means 2011-2012, Wage and income tax data

Appendix B: Regression by using emigration rates of subgroups

Table 5: Pooled cross-sectional regression model by emigration rates of income, 2011-2012¹

<i>Dependent variable:</i>	<i>emigration rate by income quintiles, in % (log)</i>				
	Q1	Q2	Q3	Q4	Q5
<i>Avg RD (log)</i>	1.163*** (0.257)	0.199 (0.228)	0.529*** (0.185)	0.435** (0.181)	0.269 (0.170)
<i>Median Income (log)</i>	-0.635*** (0.188)	0.406** (0.176)	-0.0773 (0.150)	-0.225 (0.143)	-0.281** (0.133)
<i>Total Pop. in 1000 (log)</i>	-0.367*** (0.0169)	-0.325*** (0.0139)	-0.325*** (0.0123)	-0.321*** (0.0117)	-0.312*** (0.0117)
<i>Number of Children</i>	-2.716*** (0.281)	-0.747*** (0.237)	-0.530*** (0.203)	-0.601*** (0.201)	-0.682*** (0.203)
<i>Number of HH-members</i>	0.274** (0.126)	-0.159* (0.0944)	-0.106 (0.0758)	-0.294*** (0.0750)	-0.382*** (0.0757)
<i>Poverty Rate</i>	0.0410*** (0.00832)	-0.00527 (0.00685)	-0.00139 (0.00592)	-0.00473 (0.00550)	-0.00166 (0.00525)
<i>Unemployment Rate</i>	0.0329*** (0.00588)	0.0165*** (0.00511)	0.0116*** (0.00397)	0.0134*** (0.00405)	0.00988** (0.00386)
<i>Aged between 26-39 (in %)</i>	0.0331*** (0.00916)	0.0304*** (0.00728)	0.0152** (0.00626)	0.00306 (0.00596)	0.00575 (0.00586)
<i>Aged between 40-64 (in %)</i>	-0.0311*** (0.00772)	0.00126 (0.00649)	-0.00972* (0.00519)	-0.0169*** (0.00524)	-0.0180*** (0.00505)
<i>Older than 64 (in %)</i>	-0.0221*** (0.00645)	0.00454 (0.00556)	-0.00565 (0.00460)	-0.0203*** (0.00438)	-0.0174*** (0.00415)
<i>Apprenticeship (in %)</i>	-0.00971** (0.00451)	-0.0128*** (0.00380)	-0.00279 (0.00324)	-0.0123*** (0.00328)	-0.00603* (0.00312)
<i>A-level (in %)</i>	-0.0239*** (0.00446)	-0.00893** (0.00396)	-0.00489 (0.00319)	-0.00595* (0.00313)	-0.0103*** (0.00293)
<i>Higher Edu (in %)</i>	0.0148** (0.00647)	0.00696 (0.00544)	0.0128*** (0.00481)	0.00553 (0.00450)	0.0108** (0.00453)
<i>Constant</i>	-3.454 (2.145)	-5.360*** (1.752)	-3.439** (1.458)	0.466 (1.417)	2.331* (1.373)
Observations	2,450	2,262	2,749	2,809	3,132
Adjusted R-squared	0.436	0.370	0.372	0.360	0.323

¹Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Time-, district- and urbanisation-fixed effects included. *A-level* comprises *BMS*, *AHS* and *BHS*. *Postsecondary/tertiary* contains *Kollege*, *Hochschule* and *Uni/Fachhochschule*. *People between 17-25 (in %)* and *people with compulsory or less education (in %)* represent basegroup. RD, relative deprivation; HH, household; Avg, average. All explanatory variables refer to total municipalities.

Table 6: Pooled cross-sectional regression model by emigration rates of education, 2011-2012¹

<i>Dependent variable:</i>	<i>emigration rate by education groups, in % (log)</i>			
	Group 1	Group 2	Group 3	Group 4
<i>Avg RD (log)</i>	0.960*** (0.222)	1.177*** (0.186)	0.785*** (0.191)	-0.170 (0.243)
<i>Median Income (log)</i>	-0.314* (0.181)	-0.203 (0.166)	-0.309* (0.163)	-0.505*** (0.162)
<i>Total Pop. in 1000 (log)</i>	-0.369*** (0.0132)	-0.251*** (0.0102)	-0.249*** (0.0117)	-0.311*** (0.0179)
<i>Number of Children</i>	-0.658*** (0.232)	-1.271*** (0.183)	-1.148*** (0.197)	-1.871*** (0.315)
<i>Number of HH-members</i>	-0.342*** (0.0920)	-0.0397 (0.0675)	-0.108 (0.0752)	-0.127 (0.119)
<i>Poverty Rate</i>	0.0146** (0.00642)	-0.00235 (0.00523)	0.00751 (0.00566)	0.00842 (0.00799)
<i>Unemployment Rate</i>	0.0313*** (0.00433)	0.0187*** (0.00337)	0.0121*** (0.00402)	-0.00128 (0.00626)
<i>Aged between 26-39 (in %)</i>	0.0125* (0.00687)	0.0252*** (0.00523)	0.0212*** (0.00586)	0.0293*** (0.00926)
<i>Aged between 40-64 (in %)</i>	-0.0128** (0.00613)	-0.0144*** (0.00473)	-0.0129** (0.00523)	-0.0118 (0.00786)
<i>Older than 64 (in %)</i>	-0.0137*** (0.00494)	-0.0185*** (0.00399)	-0.0177*** (0.00431)	-0.00134 (0.00663)
<i>Apprenticeship (in %)</i>	-0.0224*** (0.00332)	0.00975*** (0.00277)	-0.00522* (0.00316)	-0.00645 (0.00511)
<i>A-level (in %)</i>	-0.0313*** (0.00343)	-0.0122*** (0.00275)	0.0113*** (0.00296)	-0.00582 (0.00464)
<i>Higher Edu (in %)</i>	-0.0211*** (0.00521)	-0.000195 (0.00413)	0.0125*** (0.00439)	0.0682*** (0.00665)
<i>Constant</i>	-2.753* (1.632)	-7.281*** (1.278)	-3.526** (1.403)	5.777*** (2.048)
Observations	3,013	3,706	3,272	1,767
Adjusted R-squared	0.406	0.359	0.372	0.596

¹Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Time-, district- and urbanisation-fixed effects included. *A-level* comprises *BMS*, *AHS* and *BHS*. *Postsecondary/tertiary* contains *Kollege*, *Hochschule* and *Uni/Fachhochschule*. *People between 17-25 (in %)* and *people with compulsory or less education (in %)* represent basegroup. RD, relative deprivation; HH, household; Avg, average. All explanatory variables refer to total municipalities. *Group 1: people with compulsory or less education*, *Group 2: people in apprenticeship*, *Group 3: people with A-level (BMS/AHS/BHS)*, *Group 4: people with postsecondary/tertiary (Kollege/Hochschule/Uni/Fachhochschule)*.

Table 7: Pooled cross-sectional regression model by emigration rates of age, 2011-2012¹

<i>Dependent variable:</i>	<i>emigration rate by age cohorts, in % (log)</i>		
	Age 26-39	Age 40-64	Age over 64
<i>Avg RD (log)</i>	1.087*** (0.177)	1.191*** (0.184)	-0.609** (0.275)
<i>Median Income (log)</i>	-0.180 (0.162)	-0.192 (0.147)	-0.430** (0.215)
<i>Total Pop. in 1000 (log)</i>	-0.152*** (0.00915)	-0.262*** (0.0113)	-0.586*** (0.0205)
<i>Number of Children</i>	-1.620*** (0.168)	-0.724*** (0.186)	-0.275 (0.306)
<i>Number of HH-members</i>	0.0755 (0.0663)	-0.184** (0.0772)	-0.343*** (0.116)
<i>Poverty Rate</i>	0.000655 (0.00476)	0.00673 (0.00555)	0.00931 (0.00852)
<i>Unemployment Rate</i>	0.0146*** (0.00327)	0.0272*** (0.00360)	0.0126* (0.00671)
<i>Aged between 26-39 (in %)</i>	0.0372*** (0.00478)	0.00339 (0.00603)	0.00854 (0.00978)
<i>Aged between 40-64 (in %)</i>	-0.0287*** (0.00439)	-0.00106 (0.00529)	0.0103 (0.00960)
<i>Older than 64 (in %)</i>	-0.0232*** (0.00362)	-0.0196*** (0.00437)	0.0265*** (0.00781)
<i>Apprenticeship (in %)</i>	0.000554 (0.00259)	-0.00720** (0.00303)	0.00923* (0.00501)
<i>A-level (in %)</i>	-0.0116*** (0.00253)	-0.00947*** (0.00299)	-0.00155 (0.00490)
<i>Higher edu (in %)</i>	0.0161*** (0.00372)	0.00762* (0.00435)	0.0324*** (0.00694)
<i>Constant</i>	-5.945*** (1.253)	-7.333*** (1.397)	6.953*** (2.226)
Observations	4,178	3,443	1,468
Adjusted R-squared	0.372	0.359	0.669

¹Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Time-, district- and urbanisation-fixed effects included. *A-level* comprises *BMS*, *AHS* and *BHS*. *Postsecondary/tertiary* contains *Kollege*, *Hochschule* and *Uni/Fachhochschule*. *People between 17-25 (in %)* and *people with compulsory or less education (in %)* represent basegroup. RD, relative deprivation; HH, household; Avg, average. All explanatory variables refer to total municipalities.